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A General Procedure to Assess the Internal Structure of a Noncognitive Measure—The Student360 Insight Program (S360) Time Management Scale

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Abstract

The factorial structure of the Time Management (TM) scale of the Student 360: Insight Program (*S*360) was evaluated based on a national sample. A general procedure with a variety of methods was introduced and implemented, including the computation of descriptive statistics, exploratory factor analysis (EFA), and confirmatory factor analysis (CFA). Overall, the results indicated that the TM scale measured multidimensional constructs of TM with 5 factors. The paper concludes with a discussion of several issues concerning the wording of items and residual dependencies, as well as future directions for research.

Key words: factorial structure, time management exploratory factor analysis, confirmatory factor analysis, residual dependence

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Background

The Student360: Insight Program (*S*360) is a Web-based source of self-help tools intended to assist students—particularly those who are attending or preparing to attend community college—in planning and meeting their college objectives. The program includes a set of surveys and assessments, focused feedback, interventions, and tutorials. A set of noncognitive constructs are assessed by the *S*360, including study skills, time management (TM), test anxiety, interests, and teamwork. The current study focuses on the TM scale.

Over the last three decades, quite a few TM scales have been developed, such as the time management behavior scale (TMBS; Macan, Shahani, Dipboye, & Philips, 1990), the time structure questionnaire (TSQ; Bond & Feather, 1988), and the time management questionnaire (TMQ; Britton & Tesser, 1991). These scales were typically developed and investigated in the areas of industrial and organizational psychology and management. These scales carry the following concern: When the factorial structure of each of these TM scales was studied, the sample size employed was small. The current version of the TM scale comes from an extension of the Australian time organization management scale (ATOMS; Roberts, Krause, & Suk-Lee, 2001), adopting a definition of TM suggested by Lankein (1973). Six subscales were originally developed: the persistence subscale (perseverance to finish tasks and schedules), the estimating-time subscale (time estimation related to completing tasks), the calendar subscale (mechanism of TM), the regrets subscale (coping with time), the impulsivity subscale (preference for planning), and the clean-desk subscale (effective organization). Each subscale is measured by six items about specific TM behaviors. The test-takers are required to rate how well the description in the item matches his or her behavior on a Likert scale from 1 (*disagree*) to 4 (*strongly agree*). Nineteen items are negatively worded, meaning that negatively connoted or inefficient TM behaviors are described (see Appendix A for the six subscales and items). The number of

negatively worded items varies across the six subscales: six in the regrets subscale and six in the impulsivity subscale, four in the estimating-time subscale, and one in each of the remaining three subscales.

We applied a variety of statistical methods and techniques to examine the structure of the TM scale in this study. More specifically, descriptive statistics for items and subscales were first computed and presented visually to explore the data, then exploratory factor analysis (EFA) was conducted to assess the factorial structure, and finally the factorial structure was corroborated using confirmatory factor analysis (CFA). The description of techniques applied in this paper was aimed at providing a general framework for investigating the factorial structure of other noncognitive measures for similar purposes.

The next section starts with a brief description of the statistical analyses, followed by the results and interpretations of each analysis respectively. The paper ends with a summary and discussion of these methods, results, and related issues.

Method

The data was collected in 2006 via the *S*360 program in four regions (northeast, midwest, south, and west) of the United States. A national sample of college students (N = 777) participated in the study. A set of noncognitive measures, including the TM scale, was administered to each student. Each student had enough time to finish the TM scale. The negatively worded items were reverse-coded, so that higher scores represented more positive TM behaviors.

In a first set of analyses, descriptive statistics were computed for each item, each subscore (sum of item scores of a subscale), and the total score, using both SPSS 15.0 (SPSS, 2006) and R 2.5.0 (R Foundation, 2007). Furthermore, correlations were computed between item

scores, between subscores, and between each subscore and the total score. An interitem correlation matrix was created based on the data, as well as an intersubscale correlation matrix. The interitem correlation matrix was represented visually in a chart. More specifically, darker colors were assigned to greater values of correlation in the matrix. Reliability analyses for each subscale and the total test were also performed.

In a second set of analyses, exploratory factor analyses were conducted based on the interitem correlation matrix and intersubscore correlation matrix separately. Parallel analysis was applied to determine the number of factors using both SPSS 15.0 and SAS 9.1 (Fabrigar, Wegener, MacCallum, & Strahan, 1999; Horn, 1965; SAS, 2004; SPSS, 2006).

Finally, several waves of CFA were conducted using LISREL 8.8 (Jöreskog & Sörbom, 2001) to test whether the identified underlying factorial structure represented the data adequately. The confirmatory models were inspired by the internal structure defined by the test developers, as well as by the results of the exploratory factor analysis. In addition, several other structural equation models with higher-order factors were tested and compared.

Results

Descriptive Analyses

Among all the participants, 443 (57%) were female students and 334 were male students; about 46% were Caucasian, 18% were African American, 21% were Hispanic, 7% were Asian American, and the remaining were students from other ethnic groups. The average age of the sample was 23.62 years (*SD* = 8.84), and 90% of the students were in the range of 16 to 40 years old.

The number of missing responses per item ranged from 0 to 3 (0% to 0.4% in terms of percentage) across the 36 items; the average percentage of missing responses across items was

0.1% (see Appendix B, the third column). As mentioned earlier, ratings on a 4-point Likert scale of 1 (*disagree*) to 4 (*strongly agree*) were used as the item scores.

The grand mean for all the 36 items amounted to 2.710 (*SD* = .899), with the mean scores for individual items ranging from 1.691 to 3.534. The mean item scores ranged from 1.691 (*SD* = .937) to 3.280 (*SD* = .815) for positively worded items and from 2.152 (*SD* = .928) to 3.534 (*SD* = .737) for the negatively worded items after they were reverse-coded. The mean score was 2.610 (*SD* = .924) for the (reverse-coded) negatively worded items and 2.822 (*SD* = .870) for the positively worded items.

Given the fact that each item was on a 4-point Likert scale, the average mean of 2.710 suggested that the test-takers tended to make more use of the positive response categories (e.g., 3 and 4 for the positively worded items), while positively worded items were endorsed more highly (2.822) than negatively worded items (2.610).

The frequencies of each item in the four response categories are presented as bar plots in Figure 1. About a third of the items had severe negatively or positively skewed distributions. Item responses were unequally distributed over the four categories for most items (22 items had at least one response category with frequencies smaller than 10%). The response distributions of the positively and negatively worded items were similar to each other based on the bar plots.

The descriptive results for subscores are displayed in Table 1. As mentioned earlier, a subscore is the sum of item scores of a subscale. The maximum possible score for each subscale is 24. The calendar subscale had the lowest mean score (*M* = 11.981, *SD* = 4.366) among the six subscales; its mode and median of item responses were even smaller. The clean-desk subscale had relatively lower mean, median, and mode scores when compared to the other four subscales. The calendar subscale was the only positively skewed subscale (skewness = .662), which can also be seen in the histograms presented in Appendix C.

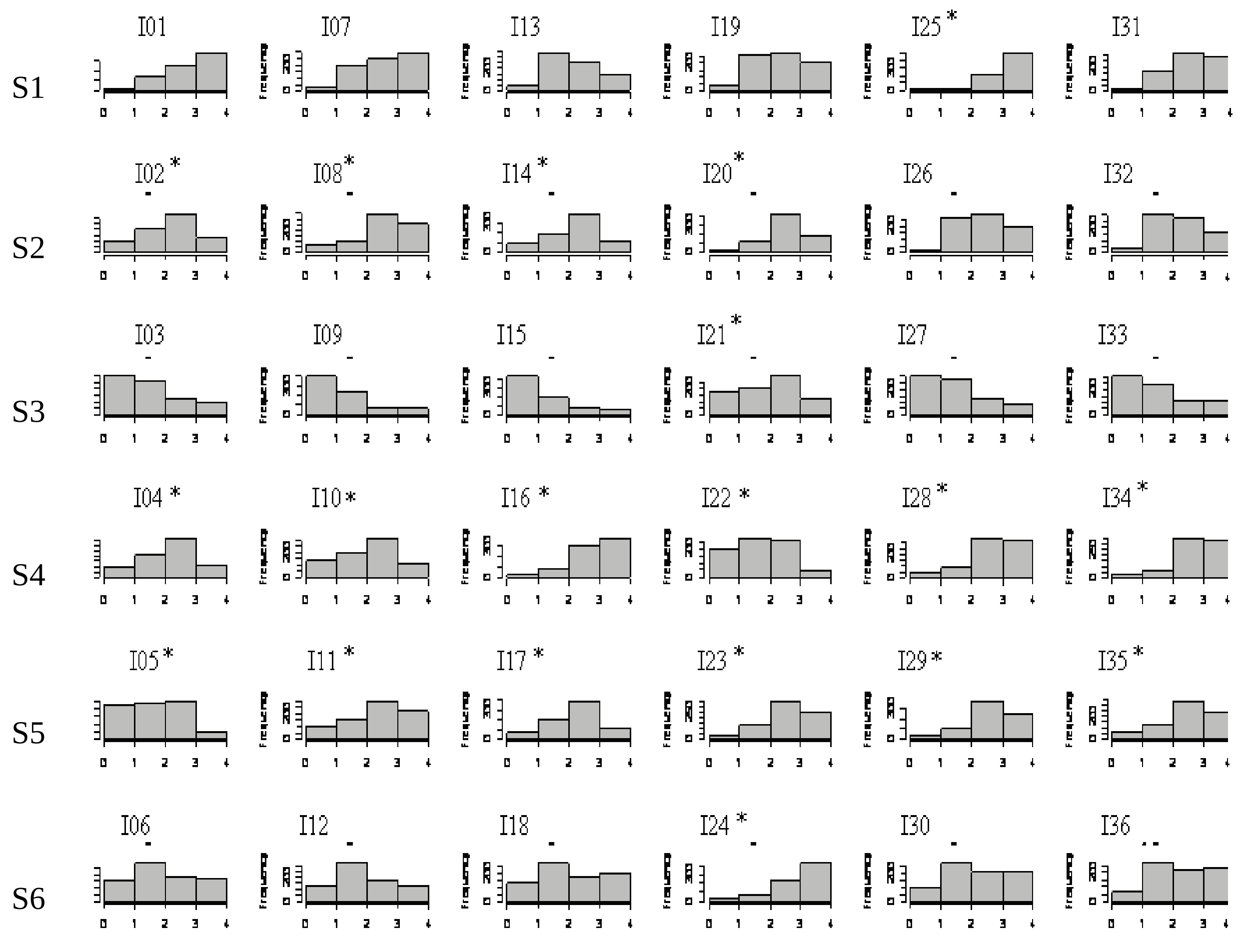

Figure 1. **Bar plots of the 36 items. Each row represents one subscale. An * indicates that the item was negatively worded and reverse-coded.**

Table 1

Descriptive Statistics for Each of the Six Subscales

Subscales	*N*	# missing	*M*	Median	Mode	*SD*	Skewness	Kurtosis
Persistence	772	5	18.488	19	20	3.171	-.289	-.491
Estimating-time	775	2	16.861	17	17	3.283	-.120	-.383
Calendar	774	3	11.981	11	7	4.366	.662	-.217
Regrets	773	4	17.157	18	18	3.279	-.653	.481
Impulsivity	766	11	16.841	17	17	3.543	-.443	030
Clean-desk	770	7	16.222	16	14	4.076	-.005	-.542

For exploratory purposes, both Pearson correlations and polychoric correlations between item scores were computed and compared. Researchers in social science and psychological science often treat the Likert-scaled item responses or ratings (with the TM scale where 1 to 4 represents disagree to strongly agree) as if it were on an interval scale, assuming a normally distributed latent variable underlies it (Olsson, 1979; Wainer & Thissen, 1976). The Pearson correlations among these item scores/ratings are then obtained as the estimates of correlations among these underlying variables. However, the Pearson correlations of ordinal/Likert-scaled responses may underestimate the correlations between the latent variables underlying them (Jöreskog & Sörbom, 1988, p.10–12; Olsson, 1979). In such cases, the polychoric correlations are typically preferred over the Pearson correlations, especially when the items have heavily skewed distributions. When the Likert-scaled responses to individual items are not too severely deviated from a normal distribution, the Pearson correlation estimation is acceptably robust (Olsson, 1979). Given the fact that a third of items of the TM scale had severely skewed distributions, we decided to use the polychoric correlation as the measure of association in this study in addition to the Pearson correlation.

The Pearson and polychoric correlation matrices were computed in PRELIS 2 (Jöreskog & Sörbom, 1988) and are visually represented in Figure 2. The Pearson correlations were computed over all cases that had valid values on both variables (i.e., pairwise deletion was employed). The lower triangle of this matrix (below the diagonal) presents the Pearson correlations, and the upper triangle (above the diagonal) presents the polychoric correlations. The cells with a darker color represent a stronger interitem association in Figure 2.

In general, the two types of correlations shared similar patterns of interitem associations, except that the polychoric correlations were slightly higher (in darker colors in Figure 2) than the Pearson correlations in general, as was suggested by Olsson (1979) and Jöreskog & Sörbom

(1988). The correlations between items within the same subscale were generally higher (cells in darker colors in Figure 2) than the correlations of items from different subscales. However, moderate levels of correlations were also found between some items from different subscales (e.g., between items from the persistence subscale and the estimating-time subscale, and between items from the regrets subscale and the impulsivity subscale; see Figure 2). These cross-subscale interitem correlations indicated that a certain level of association exists among the subscales.

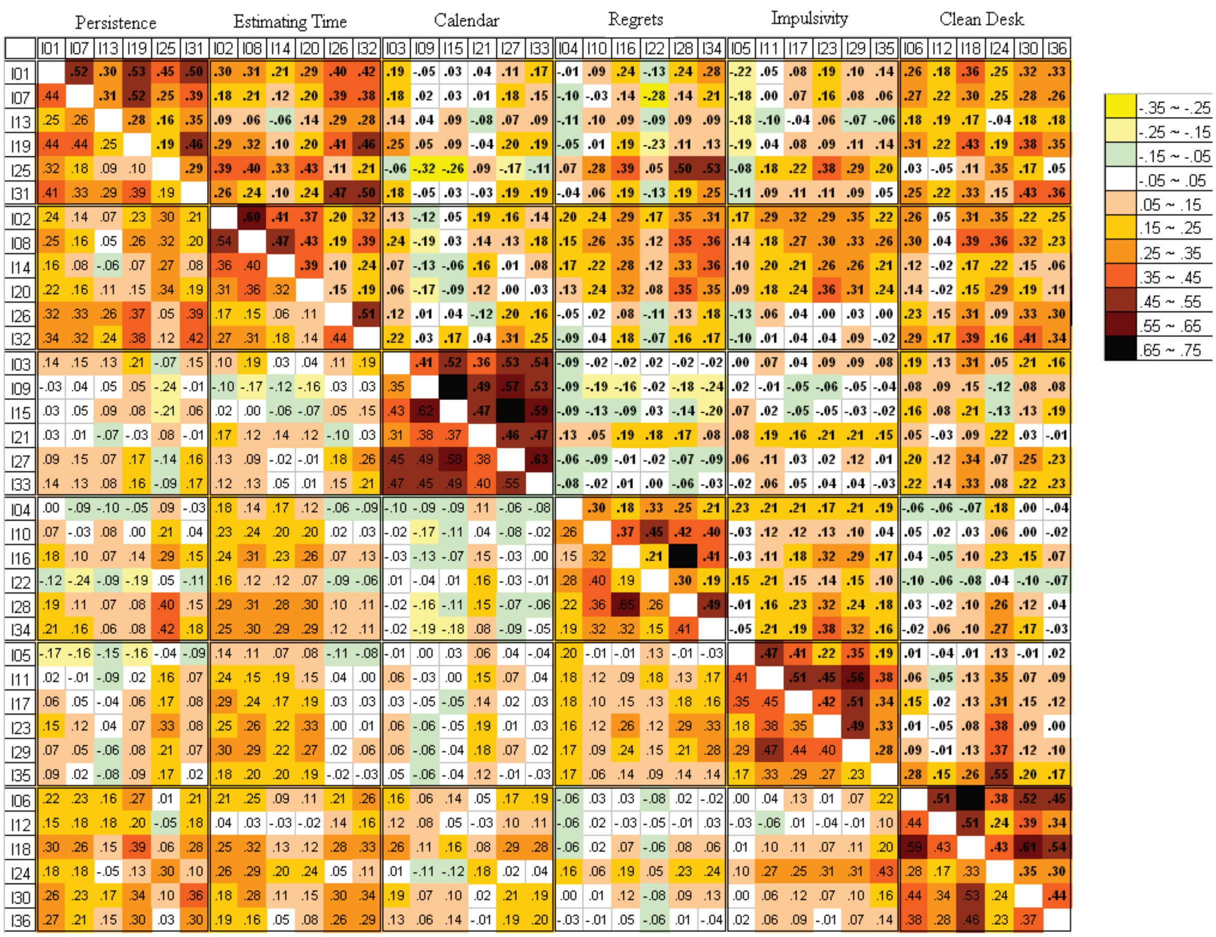

***Figure 2.* Colored correlation matrices for Pearson (below the diagonal) and polychoric (above the diagonal) correlations.**

The average value of the interitem polychoric correlations of all 36 items was .16, and the average within-subscale interitem polychoric correlations ranged from .33 (the estimating-time subscale) to .53 (the calendar subscale, see Table 2). The within-subscale interitem correlation on average was higher than the overall average interitem correlations.

Further inspection revealed that the higher within-subscale average interitem correlation was not due to extreme values of single item pairs. For example, the 15 interitem polychoric correlations for the calendar subscale were all greater than .40, which was much higher than .16 (the average interitem polychoric correlations over all items). Similar results were found for the other subscales except for the estimating-time subscale, where there were two interitem polychoric correlations lower than .16. Similar results were found based on the Pearson correlations.

In summary, the patterns found in the colored correlation matrix suggest that several dimensions might be present in the current data. The calendar subscale and the clean-desk subscale seem to be distinct from the other subscales, while the persistence subscale and the estimating-time subscale seem to mix with each other and measure a common factor. The regrets subscale and the impulsivity subscale also seem to measure something in common, but to a

Table 2

Average Inter-Item Correlations Within Each Subscale and the Total Test

Subscale	Range of interitem polychoric correlations	Average interitem polychoric correlation	Cronbach's Alpha
Persistence	.09 ~ .44	.37	.715
Estimating-time	.06 ~ .54	.33	.698
Calendar	.31 ~ .62	.53	.828
Regrets	.15 ~ .65	.35	.716
Impulsivity	.17 ~ .47	.39	.750
Clean-desk	.17 ~ .59	.44	.782
Total test	-.24 ~ .65	.16	.842

lesser degree. By looking at the correlation matrix, the six-subscale structure of the TM scale was partially supported.

Reliability analysis was performed for each subscale and for the total test. The TM scale had an internal consistency (Cronbach's alpha) of .842 and a split-half reliability of .872. The subscales' reliability coefficients (Cronbach's alpha) ranged from .698 to .828. The calendar subscale and the clean-desk subscale had the highest internal consistency reliabilities, a finding that was consistent with what was observed in the colored correlation matrix in Figure 2. Reliability analysis also revealed that eight items had item-total correlations lower than .24. The total test reliabilities increased when each of these eight items was deleted from the test separately (see Appendix B, highlighted with underscores). We also found that the clean-desk subscale's reliability values increased when item I24 was deleted from the subscale (see Appendix B). This was also true for item I25 of the persistence subscale and item I26 of the estimating-time subscale.

The Pearson correlation matrix among the six subscale scores (see Table 3) was also computed, as well as the disattenuated correlations accounting for the unreliabilities of each subscale. Low to moderate levels of correlations were found between the persistence subscale and the estimating-time subscale (.526/.745, observed / disattenuated), and between the regrets subscale and the impulsivity subscale (.327/.446). This finding confirms the pattern that could be discerned in the interitem correlation matrix in Figure 2. The estimating-time subscale had low to moderate levels of correlation with all other subscales (ranging from .318 to .406, or from .440 to .550 after disattenuation) except for the calendar subscale. The correlation between the persistence subscale and the clean-desk subscale was .442/.591, suggesting some association might exist between these two subscales, as was also indicated by the colored correlation matrix in Figure 2.

Table 3

Correlations Among Subscale Scores

Subscale	Persistence	Estimating-time	Calendar	Regrets	Impulsivity	Clean-desk
Persistence		.745	.149	.191	.096	.591
Estimating-time	.526		.166	.538	.440	.550
Calendar	.115	.126		-.108	.072	.276
Regrets	.137	.380	-.083		.446	.064
Impulsivity	.070	.318	.057	.327		.264
Clean-desk	.442	.406	.222	.048	.202	

Note. Pearson correlations are below the diagonal, and disattenuated Pearson correlations are above the diagonal.

Exploratory Factor Analysis

The internal structure of the data was examined using exploratory factor analysis (Everitt, 2005, Chapter 4). Analogous to the previous section, analyses were performed at both the item and the subscale level. At the item level, the factor analyses were carried out using both the Pearson and polychoric correlation matrices. However, we only present and discuss the results obtained from the polychoric correlations because the results based on the Pearson correlations are similar.

The screeplot of eigenvalues (Cattell, 1966), resulting from a principal component analysis (PCA) of the data, has an elbow at component number 5 (see Figure 3). This suggests that four to six factors are possible. For the parallel analysis (Horn, 1965), we compared the eigenvalues of the observed correlation matrix to the average eigenvalues of the correlation matrices computed from 1,000 randomly generated data sets with the same number of variables

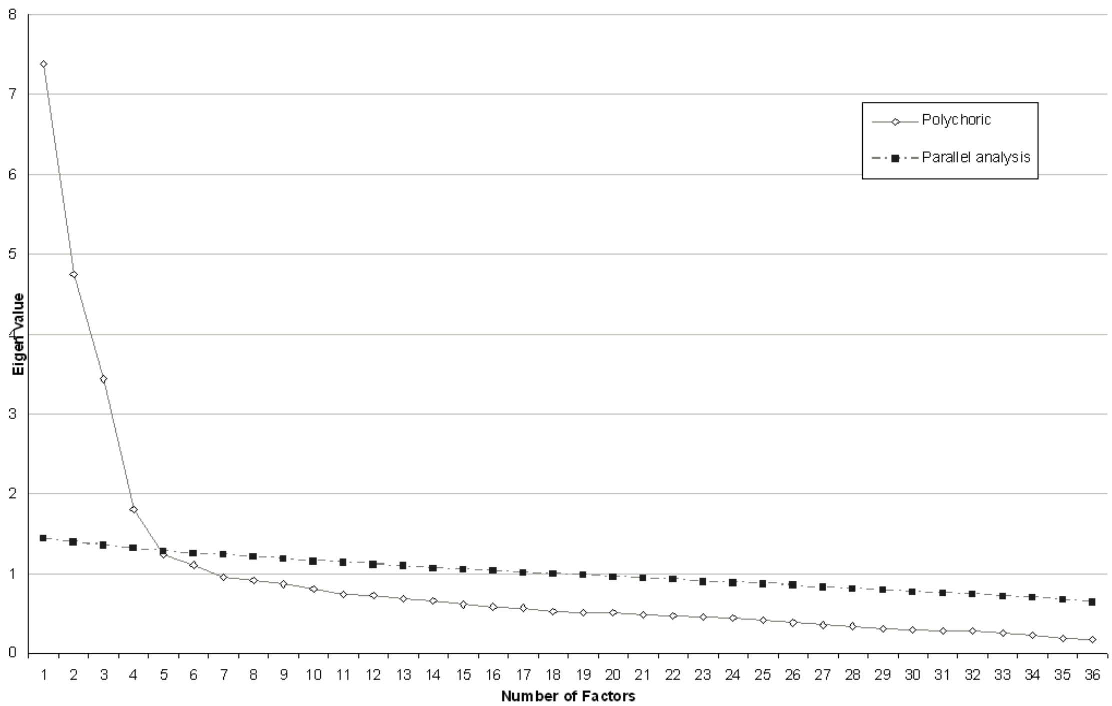

***Figure 3.* Screeplot of the eigenvalues of the polychoric correlation matrix of the 36 items.**

Note. The squares are results of the average eigenvalues determined from the parallel analysis.

and the same sample size. It was found that the two sets of eigenvalues overlapped between the factor numbers of 4 and 5. We decided to analyze the 4- and 5-factor models in the next step, as was recommended by O'Connor (2000). In addition, we also examined a 6-factor structure since it was prespecified by the test developers.

The exploratory factor analyses were carried out using the maximum likelihood estimation method and Promax rotation (Hendrickson & White, 1964). As noted above, solutions were obtained for four, five, and six factors. The factor loadings of the 36 items for the 4-, 5-, and 6-factor solution based on the polychoric correlations are displayed in Table 4, where loadings less than .3 are omitted (Comrey & Lee, 1992; Costello & Osborne, 2005) and items belonging to the same subscale predefined by assessment developers are presented together in a block. Negatively worded items are marked in Table 4.

Table 4

Factor Loadings of the 36 Items (4-, 5-, and 6-Factor Based on Polychoric Correlations)

Subscale	Item	4-factor				5-factor					6-factor					
		1	2	3	4	1	2	3	4	5	1	2	3	4	5	6
S1 persistence	I01	.64	.41			.72	.32			.31	.69				.30	.31
	I07	.60				.67					.63					.31
	I13	.39				.43					.44					
	I19	.68				.69				.40	.69				.39	
	I25[a]		.69			.46	.62		.40		.38	.59		.30		.51
	I31	.63	.30			.68				.34	.69				.33	
S2 estimating-time	I02[a]	.37	.52		.42	.38	.53		.50		.39	.54		.52	.30	
	I08[a]	.43	.56		.40	.44	.57		.47	.34	.45	.58		.49	.35	
	I14[a]		.49		.30		.49		.39			.50		.38		
	I20[a]		.53			.37	.50		.42		.33	.49		.38		
	I26	.56				.59				.30	.63					
	I32	.63				.65				.38	.69				.36	
S3 calendar	I03	.30		.63				.63					.63			
	I09			.77				.78					.78			
	I15			.85				.85					.85			
	I21[a]			.62				.60					.62			
	I27	.30		.79				.80		.30			.79			
	I33	.31		.74				.74		.30			.74			
S4 regrets	I04[a]				.30		.35		.30			.37		.31		
	I10[a]		.52				.59					.61				
	I16[a]		.69				.71					.69				.35
	I22[a]		.31				.42					.44				
	I28[a]		.76				.79		.31			.78				.35
	I34[a]		.67			.35	.65		.35			.63				.35
S5 impulsivity	I05[a]			.55					.50					.56		
	I11[a]				.67				.72					.73		
	I17[a]				.61				.66					.66		
	I23[a]		.48		.49		.43		.63			.41		.57		.41
	I29[a]		.39		.62		.37		.71			.37		.70		
	I35[a]				.59				.54	.34				.49	.36	.33
S6 clean-desk	I06	.63			.34	.35				.77	.37				.77	
	I12	.47								.61					.61	
	I18	.74			.37	.48		.30		.82	.50				.82	
	I24[a]	.40	.30		.62		.36		.59	.48		.33		.51	.50	.44
	I30	.66				.49				.65	.51				.65	
	I36	.59				.41				.61	.44				.60	

Note. Extraction method is maximum likelihood; rotation method is promax with kaiser normalization; loadings less than .3 were omitted from this table.

[a] Negatively worded items and have been reversely coded for the analysis.

In the 4-factor structure, the first factor had 18 items with substantial loadings. More specifically, six items were from the clean-desk subscale; five items were from the persistence subscale; and four items were from the estimating-time subscale (see Table 4). All items loading on this factor were positively worded items, except for item I24 from the clean-desk subscale and items I02 and I08 from the estimating-time subscale. The second factor had 15 items with substantial loadings, mainly from the estimating-time subscale (4 items) and the regrets subscale (5 items). All of the items with substantial loadings on the second factor were negatively worded items, except for two items from the persistence subscale (I01 and I31).

The third factor seemed to be very unique among the other factors. The items with substantial loadings on this factor were exclusively from the calendar subscale except for item I05 (see Table 4). It should be noted that three items of the calendar subscale also had substantial loadings on the first factor. The fourth factor had 12 items with a substantial loading on it, predominantly from the impulsivity subscale (5 items), the estimating-time subscale (3 items), and the clean-desk subscale (3 items). Most of these items were negatively worded.

The six items of the estimating-time subscale loaded on multiple factors. The four negatively worded items substantially loaded on the second factor, while the two positively worded items only loaded on the first factor. Among the four negatively worded items, three of them also had substantial loadings on the fourth factor, and two also loaded on the first factor substantially (see Table 4).

In the 5-factor solution, the item-factor loading pattern was similar to that of the 4-factor solution, except that all six items from the clean-desk subscale now loaded substantially on the fifth factor, with four items loading substantially on the first fact as well.

The exploratory results for the 6-factor solution were not so different from the results of the 5-factor solution. Nine items had substantial loadings on the sixth factor, but all of them had substantial loadings on one or more of the other factors.

Some items did not have a substantial loading on the same factor that was loaded on by the other items from the same subscale. For example, item I04 in the regrets subscale loaded lower than .3 on the second factor while the other items of this subscale had loadings higher than .3 on the same factor (see the 4-factor solution in Table 4). This pattern was the same for the 4-, 5-, and 6-factor solution. Item I04 asks, “I think about the road not taken,” which might not necessarily be related to regret in the context of TM behaviors, and hence may be different from the other items of that subscale. In the persistence subscale, item I25 did not load on the same factor as the other items did (in the 4- and 6-factor structure) and had a cross-loading on other factors (in the 5-factor structure). The item describes: “I give up when the ‘going gets tough.’” The colloquial term “going gets tough” may have been unclear to some of the participants.

The exploratory factor analysis results partially supported the structure predefined by the test developers. The calendar subscale and the regrets subscale appeared in the exploratory analysis as each loaded on a separate factor very well. The impulsivity subscale, the clean-desk subscale, and the persistence subscale also showed up as distinctive factors in the EFA. However, some items of these subscales had different loadings than the other items of the subscale on a particular factor or had a substantial loading on factors different from the other items of the subscale. The estimating-time subscale did not emerge with a clear loading pattern. The six items loaded on different factors, with the two positively worded items always loading on a factor different from the negatively worded items. Furthermore, the persistence subscale and the clean-desk subscale primarily loaded on the same factor.

In summary, two models were obtained from the item level EFA: the 4-factor model and the 5-factor model. In the 4-factor solution, the predefined calendar subscale and the impulsivity subscale each constituted a separate factor. A combination of the estimating-time subscale and the regrets subscale formed the third factor. And a combination of the persistence subscale and the clean-desk subscale formed the fourth factor. In the 5-factor structure, the regrets subscale and the estimating-time subscale were combined into one factor, and the other four subscales each appeared as a separate factor. The 6-factor model found in the EFA was not considered given that the items with substantial loadings on the sixth factor was scattered around the six subscales and made it hard to interpret.

An EFA was also performed based on the correlation matrix among the six subscale scores. Mardia's statistic was computed using PRELIS 2, the coefficient was .9266 (<3), indicating an acceptable multivariate normality condition was met for the six subscale scores (Jöreskog & Sörbom, 1988; Mardia, 1970). Parallel analysis indicated that there were two or three factors underlying the six subscale scores. (See Appendix H for the screeplot.) Table 5 presented the subscale-factor loadings after Promax rotation based on an exploratory factor analysis using the maximum likelihood estimation method. In both 2-factor and 3-factor models, the persistence, the estimating-time, and the clean-desk subscales loaded on the first factor, while the regrets and the impulsivity subscales, together with the persistence and the estimating-time subscales, loaded on the second factor. The calendar subscale loaded on the third factor in the 3-factor model, together with the persistence, estimating-time, and clean-desk subscales. The loading patterns between subscales and factors were not clear for both models and were difficult to interpret. We decided not to employ CFA on these two factor models. However, the low between-factor correlations (e.g., .22 for the 2-factor model) indicated that a multidimensional structure is present in the TM scale.

Table 5

Exploratory Factor Analysis (EFA) of the Factorial Structure of the Six Subscale Scores

Subscale	Factor 1 of 2	Factor 2 of 2	Factor 1 of 3	Factor 2 of 3	Factor 3 of 3
Persistence	.70	.35	.99	.31	.49
Estimating-time	.73	.66	.59	.63	.51
Calendar					.35
Regrets		.74		.73	
Impulsivity		.44		.50	
Clean-desk	.63		.48		.69

Note. Extraction method is maximum likelihood; rotation method is promax with kaiser normalization. Factor loadings lower than .3 are omitted.

Confirmatory Factor Analysis (CFA)

Since the TM scale consisted of six subscales defined by the assessment developers, a CFA was performed to evaluate whether a measurement model fit the data for each subscale before fitting the models resulted from the EFA. A measurement model is a single factor model where all indicators (items) load on the single factor and all the indicators' residuals are independent from each other (residuals' covariances were all set as zero; see Raykov & Marcoulidies, 2000). The measurement model was fitted to the polychoric correlation matrix of items for each subscale separately (see Appendix E). The polychoric correlation was considered instead of the Pearson correlations because more than a third of the items were heavily skewed and the Pearson correlations might lead to a biased estimation of the interitem associations, as mentioned in the previous section.

The polychoric correlations were estimated based on the asymptotically distribution free (ADF) method (Browne, 1984), where a large sample size is generally required to estimate the asymptotic covariance matrix for the polychoric correlations (Jöreskog & Sörbom, 2001, p. 59; Bentler & Chou, 1987, p. 173). The asymptotic covariance matrix is typically analyzed with the

(diagonal) weighted least square estimation method. A weight matrix is obtained as the inverse of the asymptotic covariance matrix, which then is used in the weighted least square (WLS, using the full weight matrix), and the diagonal weighted least square (DWLS) estimation method (using only the diagonal elements of the weight matrix). The DWLS is preferred when the sample size is small or medium (Aish & Jöreskog, 1990; Jöreskog & Sörbom, 2001; Muthén, 1983) relative to the number of items and parameters.

In this study, the WLS estimation method was used to fit the factor models for individual subscales and the DWLS estimation method was used to fit the factor models of the total test.

For each subscale, a measurement model with one latent trait measured by the six items was fitted to the data using the WLS) estimation method. According to Browne & Cudeck (1993; see also Hu & Bentler, 1999; Raykov & Marcoulidies, 2000; Yu & Muthén, 2001), a model with the root mean square error approximate (RMSEA) value below .08 and the Tucker-Lewis index (TLI, or comparative fit index [CFI]) value above .90 can be considered an acceptable fit; a model with the RMSEA value below .05 and the TLI (and CFI) value above .95 can be considered a good fit. Following these suggestions, four of the six subscales each had a good or acceptable fit with the measurement model, the RMSEA values ranging from .009 to .068, and the TLI values ranging from .94 to .99 (see Table 6). These good fit indices suggest that a measurement model fitted the data well for these four subscales and a unidimensional latent construct was measured by each of these four subscales.

The measurement model for the estimating-time subscale fitted poorly (RMSEA=.108, TLI =.79, and CFI=.88; see Appendix E). The impulsivity subscale also had a poor model-data fit (RMSEA=.118, TLI=.84, and CFI=.90). The modification indices (Raykov & Marcoulidies, 2000) for the covariances between errors for several items from these two subscales were found to be very high. For the estimating-time subscale, the model fit would be improved with a Chi-

square change of 78.61 if releasing the error covariance between items I26 and I32 (all the error covariances were fixed as zero in the measurement model). For the impulsivity subscale, the Chi-square would change by 81.95 upon releasing the residual covariances between items I16 and I28, and between items I22 and I34 (see Appendix E). The poor fit indices of these two subscales, as well as the large Chi-square change indicated by the modification indices, suggested that a measurement model did not fit the data well and some modifications might be made to account for the non-zero residual covariances.

A more complete structural equation model with six hypothetical factors was then fit to the polychoric correlation matrix of all 36 items, with a latent factor specified to be measured by each subscale. No restrictions were imposed on the correlations between factors. (See Appendix F for the path diagram of the model.) The model was estimated using DWLS. The fit statistics were acceptable, with the RMSEA value of .070, the CFI value of .92, and the TLI value of .91 (see Table 6).

Furthermore, two confirmatory models based on the exploratory analysis results (the 4- and 5-factor models in Table 4) were fit to the data. Recall that the 4-factor model was formed by combining items of the estimating-time subscale and the regrets subscale to measure a single factor, combining items of the persistence subscale and the clean-desk subscale to measure another single factor, and keeping the remaining two subscales as two single factors. The 4-factor model fit the data marginally well using the DWLS estimation method, with the RMSEA value of .081, the TLI value of .88, and the CFI value of .89 (see Table 6 and Appendix G). Better fit indices were obtained for the 5-factor model (combining items of the estimating-time subscale and the regrets subscale to measure one single factor, with the remaining four subscales as four single factors), with the RMSEA value of .062, the TLI value of .93, and the CFI value of

Table 6

Model Fit Indices for the Measurement Model of Each Subscale (Polychoric and Weighted Least Square [WLS])

Subscale	RMSEA	TLI(NNFI)	CFI	Chi-square
Persistence	.060	.94	.96	34.06 (*df* = 9)
Estimating-time	.108	.79	.88	90.75 (*df* = 9)
Calendar	.068	.96	.98	41.53 (*df* = 9)
Regrets	.118	.84	.90	106.81 (*df* = 9)
Impulsivity	.058	.94	.96	32.18 (*df* = 9)
Clean-desk	009	1.00	1.00	9.51 (*df* = 9)
Total test 6f (DWLS estimation)	.070	.91	.92	2802.27 (*df* = 579)
Total test 4f (DWLS estimation)	.081	.88	.89	3595.72 (*df* = 588)
Total test 5f (DWLS estimation)	062	.93	.94	2335.49 (*df* = 584)

Note. RMSEA = root mean square error approximate, TLI = Tucker-Lewis index, CFI = comparative fit index, DWLS = diagonal weighted least square.

.94 (see Table 6 and Appendix H). The fit indices suggested that the 5-factor solution provided a better balance between model-fit and model-complexity than the 6-factor model.

In addition to these models, a measurement model for all 36 items was also tested against the data to examine whether a single factor underlies the 36 items. Two higher-order factor models, one based on the 5-factor model and the other on the 6-factor model, were also tested given the data. The higher-order factor models were tested to see whether a common latent variable was present underlying the five or six factors, which could provide useful information for the decisions of score reporting.

The measurement model did not converge, while the two higher-order factor models both had poor model fit indices. The nonconvergence and poorly fitted higher-order models suggested

that the TM scale was not unidimensional, and it might not be a legitimate practice to report a single total score for the TM scale. These results also confirmed the multidimensionality of the TM scale inferred from the subscore-based EFA.

In summary, the CFA suggested that four of the six subscales each measured a unidimensional construct separately. The other two subscales (the estimating-time subscale and the impulsivity subscale) resulted in lack of fit due to the local dependencies among items. The measurement model with all 36 items of the TM scale did not converge given the data. The two higher-order factor models did not fit the data well. The 6-factor structure defined by scale developers fit the data at a marginally acceptable level. However, the 5-factor structure (by combining items of the estimating-time subscale and the regrets subscale to measure a single factor) suggested by the EFA had a better model-data fit.

Summary and Discussion

The TM scale of the *S*360 program assesses individuals' TM style and profile. It is aimed to help students know more about how their noncognitive abilities and/or styles might positively affect their academic achievement. The scale consists of six subscales, each measured by six items.

In this study, we analyzed a national sample of student responses to evaluate whether the predefined six-subscale structure was empirically present in the data. Analyses were performed at both the item and the subscale level, including purely descriptive analyses (descriptive statistics and correlations), EFA, and CFA. This sequence of analyses provided a general framework we recommend for investigating the structure of other scales used for similar purposes. Starting from a purely descriptive analysis not only gave us a useful impression of the data, but also led to a better understanding of the results from the subsequent, statistically more

complex analyses. In addition, it may lead to tentative hypotheses that can be tested rigorously in the latter analyses.

Descriptive analyses suggested that the proportion of missing observations was very small and negligible. Items were endorsed at the upper-middle level on the Likert scale, where negatively worded items were rated slightly lower (after reverse coding) than positively worded items in general. The item response distributions were similar for the two types of items. The calendar subscale had the lowest mean scores, while the persistence subscale had the highest. The subscale scores, when looked together, did not severely deviate from a multivariate normal distribution.

A convenient way to represent correlations visually is the colored correlation matrix used in this study. Such a representation presents easily discerned patterns among the correlations. The colored correlation matrix for the 36 items revealed that the correlations between items from the same subscale were higher than the overall average interitem correlations (see the darker colored blocks along the diagonal in Figure 2). It also revealed a moderate level of association between some subscales, as was confirmed by the correlations between the subscale scores (see Table 3). For example, the items of the persistence subscale correlated to a substantial degree with the items of the estimating-time subscale. The internal consistency reliabilities were moderate to high. The scores on the estimating-time subscale were the least reliable, and the scores on the calendar subscale were the most reliable.

The EFA suggested that a 4- or 5-factor model could well represent the data. In the 4-factor structure, the persistence subscale and the impulsivity subscale each appeared as a separate factor, the third factor was a combination of the persistence subscale and the clean-desk subscale, and the fourth factor was a combination of the regrets subscale and the estimating-time subscale.

The 5-factor structure was similar to the 4-factor solution, except that the persistence and clean-desk subscales appeared as two distinct factors.

The CFA of each subscale supported the claim that four of the six subscales each measured a single construct separately. For the other two subscales, model fit indices were not acceptable. This was possibly due to residual covariances between some items within these two subscales. The confirmatory analysis for the total test suggested that the 6-factor structure predefined by the test developers fit the data at a marginally acceptable level. However, the 5-factor models suggested by the EFA results had a better fit to the data. Further fitting of higher-order factor models were not successful.

In summary, the current study found that the TM scale was a measure of a multidimensional construct related to TM behaviors. The results from a variety of analytical approaches and procedures used in this study were generally consistent with each other and led to a well-supported result for the factorial structure of the TM scale. A 5-factor solution was recommended based on empirical fit indices.

There were several issues that may need further investigation. First, eight items were found to threaten the total test reliability when they were included in the test score, and three items were found to threaten the subscales' reliability. It is worthwhile to have a closer look at those items.

Second, several items of the estimating-time subscale had very low correlations with one another. These correlations were even lower than the overall average interitem correlation of the test. Such a low correlation between items within a subscale indicates that these items might measure different constructs.

Third, the evaluation of the measurement models for each subscale using CFA revealed that residual dependencies might exist between several items in two of the subscales, which may

also require further investigation. Factors like vocabulary, language style, format, and the behaviors described by these items may need to be re-examined to ensure the items can be easily and accurately understood as intended.

For example, items I26 and I32 were both from the estimating-time subscale and were the only two positively worded items in that subscale. Both items used the term “realistic,” and described very similar TM behaviors (see Appendix A). This type of similarity might lead to dependence issues between these two items. A similar pattern was found for items I16 and I28, where both described behaviors related to past TM behaviors. Removing one item from each pair (suspected of dependency issues) from the full model and replacing each with an unrelated item might be a solution, and these replacement items could be either modified from the original items or recreated by the scale developers.

In the literature on social behavioral measures, it has been found that negatively worded items may be affected by a social desirability factor (Bartholomew & Schuessler, 1991; DeVellis, 1991; Motl & DiStefano, 2002). In this study, we found that most of the negatively worded items tended to load on two common factors, while most positively worded items tended to load on one factor. Future research is recommended to examine whether a social desirability factor exists that could jeopardize the reliability and construct validity of the assessment. If so, a revision of the scale might be necessary.

Finally, the internal structure suggested by this study may need further replication. We recommend cross-validating the construct structure in other studies with samples from similar and/or different populations.

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List of Appendices

Appendix A

Items and Subscales Layout

Subscale	Item no.	Item
Persistence	I01	I am driven to achieve my goals.
	I07	I am future-directed.
	I13	I persevere with difficult tasks.
	I19	I make my goals specific.
	I25[a]	I give up when the "going gets tough."
	I31	I focus on what really matters.
Estimating-time	I02[a]	I leave things to the last minute.
	I08[a]	I am a bad time manager.
	I14[a]	I underestimate the time required to complete a task.
	I20[a]	At the end of the day, I still haven't completed the important task I intended to do.
	I26	I am realistic about what I can achieve in a given period of time.
	I32	I set realistic time estimates on each task.
Calendar	I03	I write a daily to-do list.
	I09	Without my appointment calendar I am lost.
	I15	My appointment calendar is my lifeline.
	I21[a]	I rely on my memory to keep appointments.
	I27	I check my appointment calendar on instinct.
	I33	I use a personal organizer.
Regrets	I04[a]	I think about the road not taken.
	I10[a]	I worry about what the future holds.
	I16[a]	I live in the past.
	I22[a]	I spend time thinking about what my future will be like.
	I28[a]	I find myself dwelling on the past.
	I34[a]	I regret decisions as soon as I make them.
Impulsivity	I05[a]	I enjoy being spontaneous.
	I11[a]	I like to "live on the edge."
	I17[a]	I do things on impulse.
	I23[a]	I like to leave things to chance,
	I29[a]	I fly by the seat of my pants.
	I35[a]	I have creative ideas when I am disorganized.
Clean-desk	I06	I keep my desk uncluttered.
	I12	I like a bare minimum of things on my desk.
	I18	I organize my desk so I know exactly where things are.
	I24[a]	I feel relaxed surrounded by a mess.
	I30	At the end of a workday, I leave a clear, well-organized work space.
	I36	I believe there is "a place for everything and everything in its place."

Note. The four responses for each question were rarely/never, sometimes, often, and usually/always, corresponding to 1 to 4, respectively.

[a] Negatively worded items were reversely coded for analysis.

Appendix B

Descriptive Statistics by Items

Item	*N*	Missing	*M*	Median	Mode	*SD*	Skewness	Kurtosis	Item deleted reliability	Item deleted subscale reliability
I01	775	2	3.280	3	4	.815	-.770	-.449	0.837	0.633
I02[a]	777	-	2.616	3	3	.916	-.256	-.735	0.835	0.623
I03	776	1	2.050	2	1	1.031	.623	-.786	0.840	0.815
I04[a]	777	-	2.614	3	3	.887	-.309	-.613	**<u>0.845</u>**	0.715
I05[a]	775	2	2.152	2	3	.928	.170	-1.051	**<u>0.846</u>**	0.739
I06	776	1	2.455	2	2	1.035	.166	-1.133	0.837	0.724
I07	777	-	3.045	3	4	.895	-.424	-.926	0.839	0.654
I08[a]	777	-	2.997	3	3	.915	-.713	-.240	0.834	0.610
I09	777	-	1.766	1	1	.944	1.072	.139	**<u>0.846</u>**	0.798
I10[a]	777	-	2.539	3	3	.950	-.185	-.893	<u>0.843</u>	0.656
I11[a]	777	-	2.828	3	3	.988	-.462	-.802	0.840	0.676
I12	776	1	2.403	2	2	.972	.269	-.908	**<u>0.842</u>**	0.762
I13	776	1	2.644	3	2	.845	.210	-.816	**<u>0.843</u>**	0.710
I14[a]	776	1	2.706	3	3	.867	-.393	-.445	0.839	0.665
I15	776	1	1.691	1	1	.937	1.209	.393	**<u>0.843</u>**	0.786
I16[a]	777	-	3.326	3	4	.767	-1.024	.671	0.840	0.666
I17[a]	774	3	2.722	3	3	.835	-.390	-.327	0.839	0.696
I18	774	3	2.571	2	2	1.046	.049	-1.214	0.833	0.704
I19	776	1	2.841	3	3	.860	-.080	-.957	0.838	0.657
I20[a]	777	-	2.987	3	3	.795	-.642	.223	0.839	0.673
I21[a]	777	-	2.447	3	3	.992	-.066	-1.063	0.841	0.824
I22[a]	776	1	2.195	2	2	.885	.102	-.931	**<u>0.846</u>**	0.695
I23[a]	775	2	3.071	3	3	.825	-.644	-.096	0.839	0.723
I24[a]	776	1	3.347	4	4	.859	-1.208	.645	0.837	**<u>0.790</u>**
I25[a]	777	-	3.534	4	4	.737	-1.707	2.661	0.840	**<u>0.728</u>**
I26	777	-	2.835	3	3	.849	-.060	-.934	0.840	**<u>0.703</u>**
I27	776	1	1.981	2	1	.978	.695	-.554	0.839	0.786
I28[a]	775	2	3.178	3	3	.841	-.908	.320	0.839	0.637
I29[a]	776	1	3.090	3	3	.822	-.755	.193	0.838	0.699
I30	776	1	2.669	3	2	.999	-.047	-1.127	0.836	0.743
I31	776	1	3.142	3	3	.777	-.417	-.758	0.838	0.664
I32	776	1	2.715	3	2	.853	.081	-.872	0.837	0.662
I33	777	-	2.064	2	1	1.071	.615	-.905	0.839	0.792
I34[a]	776	1	3.289	3	3	.761	-1.066	1.104	0.840	0.687
I35[a]	774	3	2.972	3	3	.905	-.636	-.329	0.840	0.747
I36	776	1	2.796	3	2	.965	-.136	-1.117	0.838	0.760

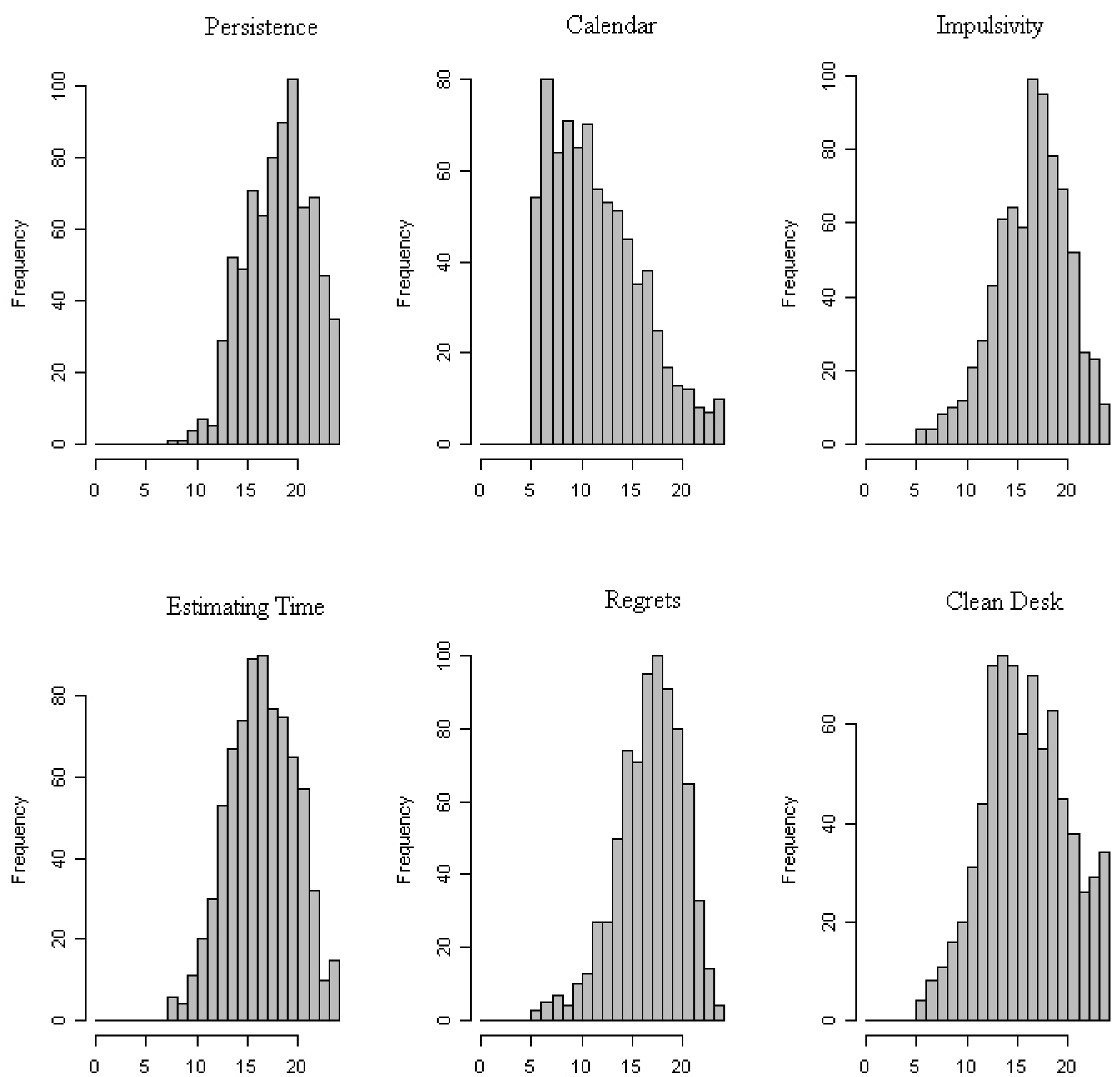
Item	*N*	Missing	*M*	Median	Mode	*SD*	Skewness	Kurtosis	Item deleted reliability	Item deleted subscale reliability
Mean of all items			2.710			.899	-.223	-.406		
Mean (positively worded items)			2.822			.870	-.329	-.403		
Mean (negatively worded items)			2.610			.924	-.129	-.410		

Note. Item-deleted reliabilities that are greater than the total scale reliability are highlighted with bold and underscored; similarly, in the last column, the item-deleted subscale reliabilities that are greater than the cooresponding subscale reliability are also highlighted with bold and underscored.

[a] These are the items where the responses were recoded so that higher scores means more positive time management behaviors.

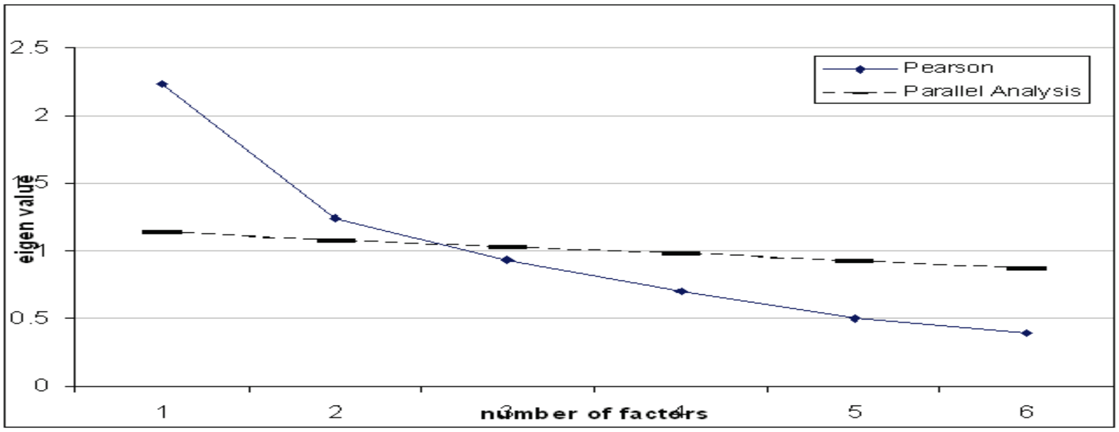
Appendix C

Histogram of the Six Subscales



Appendix D

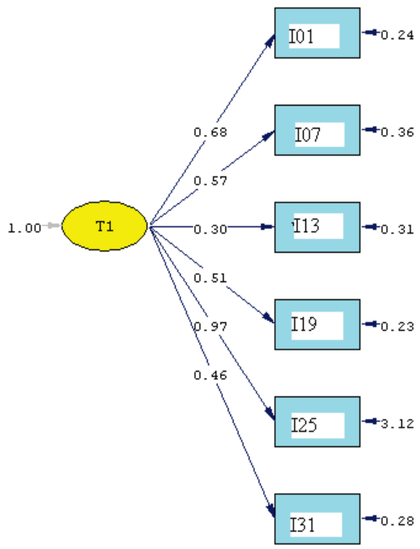
Scree Plot for the Six Subscales Principal Component Analysis



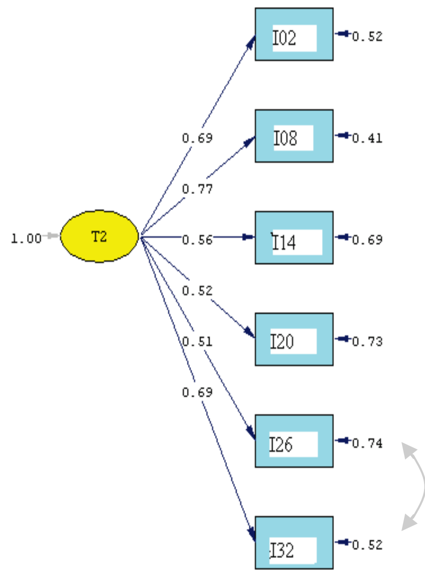
Note. The dotted line connotes the average eigenvalues generated from the parallel analysis.

Appendix E

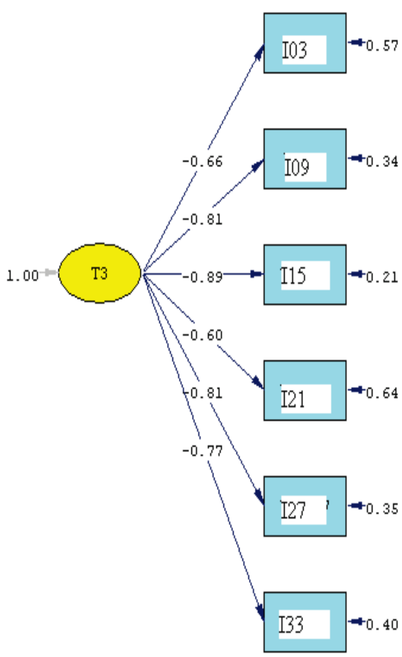
Measurement Models for Each of the Six Subscales



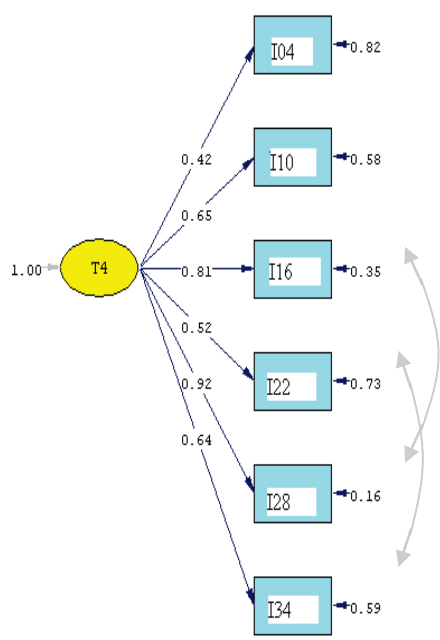
Chi-Square=34.06, df=9, P-value=0.00009, RMSEA=0.060



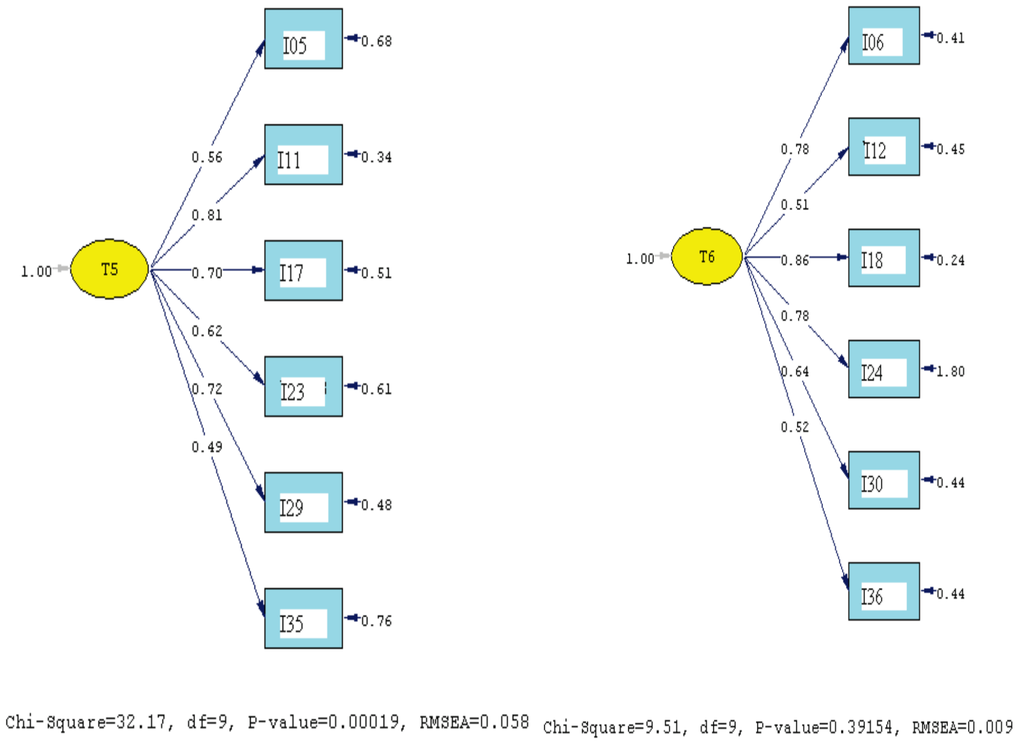
Chi-Square=90.76, df=9, P-value=0.00000, RMSEA=0.108



Chi-Square=41.54, df=9, P-value=0.00000, RMSEA=0.068



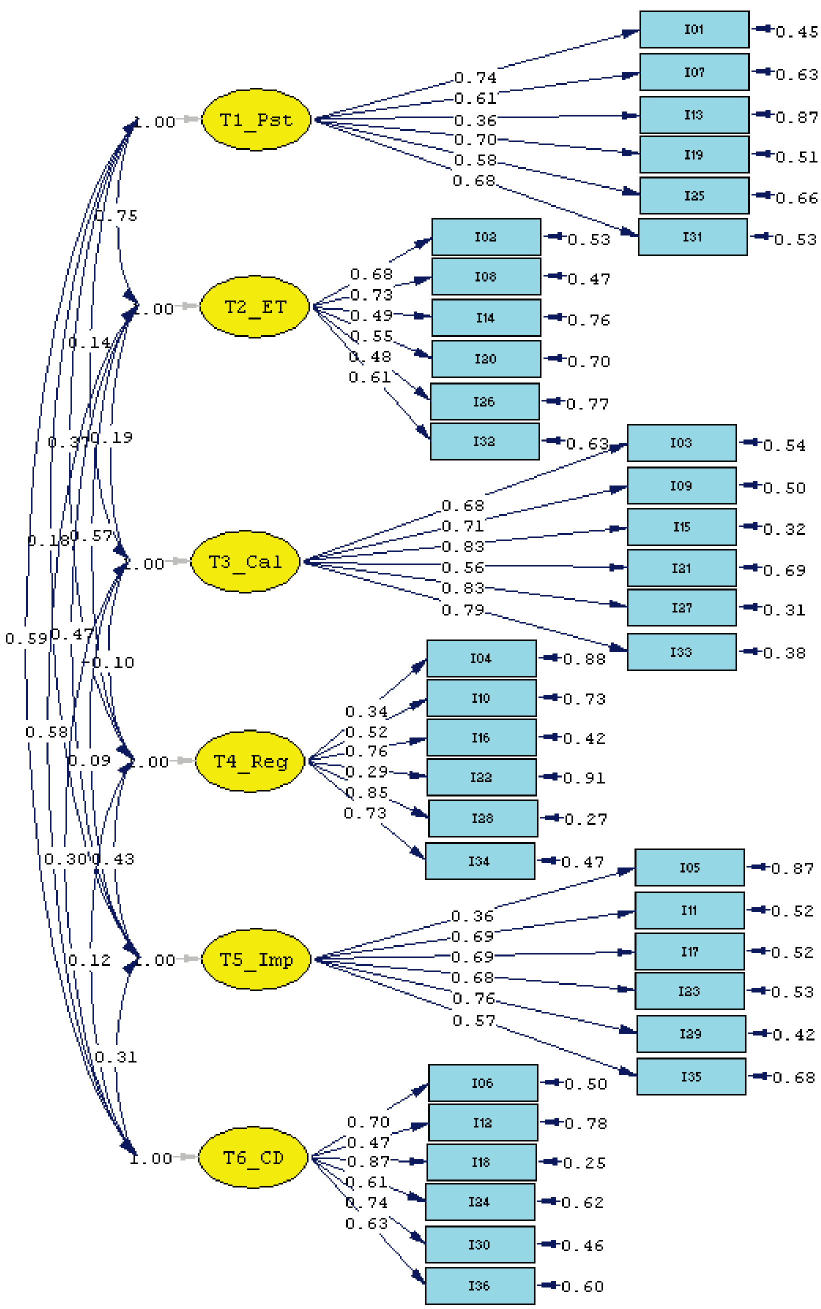
Chi-Square=106.81, df=9, P-value=0.00000, RMSEA=0.118



Note. T1–T6 represents the six subscales respectively: persistence; estimating-time; calendar; regrets; impulsivity; clean-desk. The shaded two-way arrows are the modification indices suggested by the LIEREL program, which might indicate the dependency between the measurement errors connected.

Appendix F

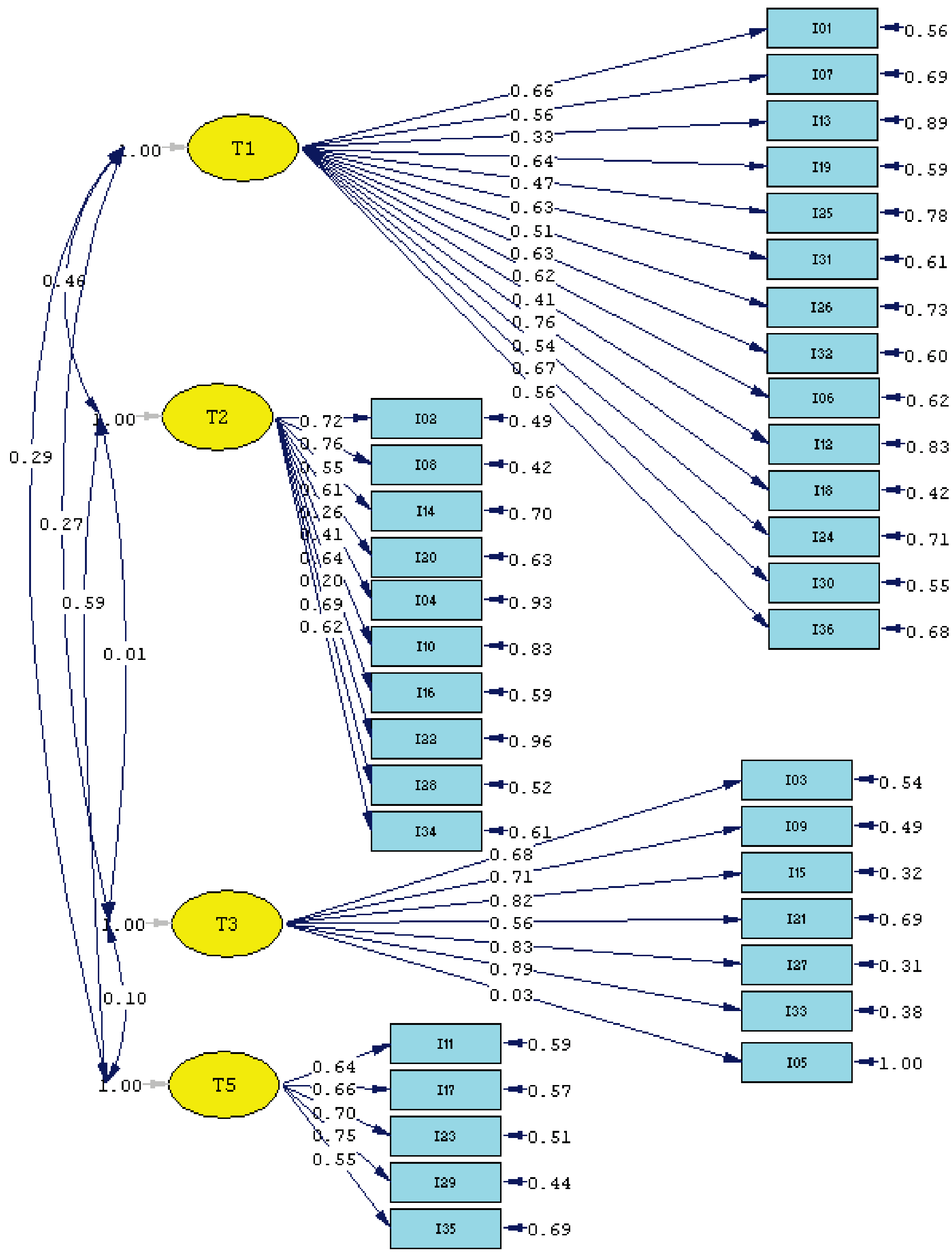
Path Diagram and Parameter Estimates for the Time Management (TM) Scale (Diagonal Weighted Least Square [DWLS])



Note. Chi-square = 2,802.27, *df* = 579, *p*-value = .000, RMSEA (root mean square error approximate) = .070.

Appendix G

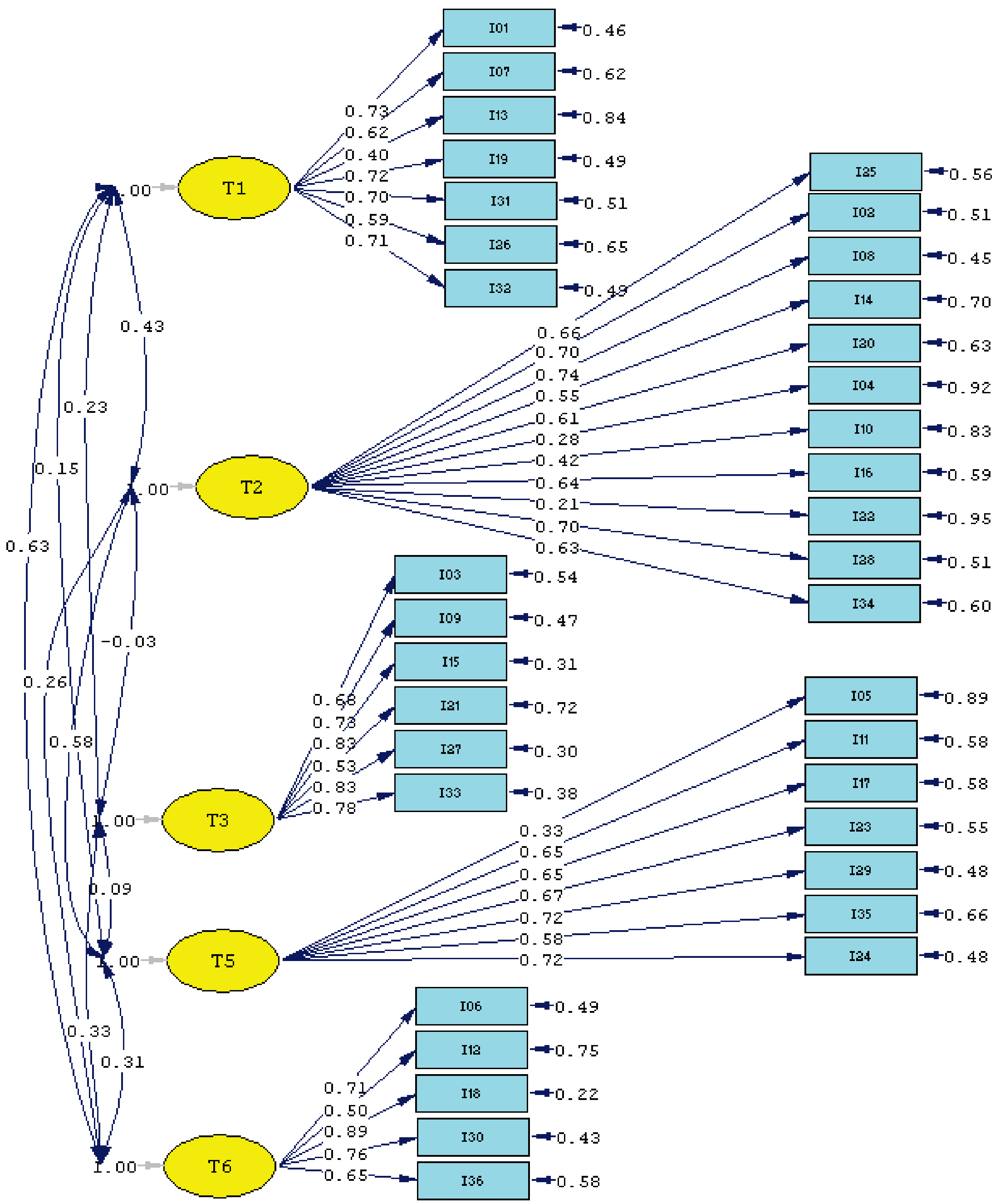
Path Diagram and Parameter Estimates for the Time Management (TM) Scale (4-Factor, Diagonal Weighted Least Square [DWLS])



Note. Chi-square = 2595.72, *df* = 588, p-value = .00, RMSEA (root mean square error approximate) = .081

Appendix H

Path Diagram and Parameter Estimates for the Time Management (TM) scale (5-factor, Diagonal Weighted Least Square [DWL)])



Note. Chi-square = 2335.49; *df* = 584, p-value = .00, (root mean square error approximate) RMSEA = .062.